Contingent Analysis of Arch Family Models for Eccentricity Analysis in Human Tailored Portfolio: A Comparative Study with Respect to the Indian Stock Market

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Abstract

Volatility analysis plays a crucial role in portfolio management as it provides insights into the risk and potential returns of investment portfolios. In this study, we conduct a contingent analysis of ARCH models for volatility analysis in a customized portfolio, specifically focusing on the Indian stock market. By applying ARCH family models to a customized portfolio consisting of Indian stocks, we aim to intuit performance and appraisea convenient model for volatility analysis in the Indian context and choose the best portfolio among a defined portfolios. To conduct the analysis, we have collected historical price data of selected stocks from the NSE, India. The results of our analysis provide valuable insights into the effectiveness of ARCH family models for volatility analysis in Indian bourse. This information will assist portfolio managers and investors in making informed decisions regarding risk management and portfolio optimization.

Keywords: ARCH , GARCH, EGARCH, TGARCH, Volatility Forecasting, AIC, SIC, BIC

Introduction

Volatility analysis is a crucial component of portfolio management, as it provides valuable insights into the risk and potential returns associated with investment portfolios. Volatility refers to the degree of fluctuation or dispersion in the prices of financial assets. Understanding and accurately predicting volatility is essential for effectively managing portfolios and making informed investment decisions.

The ARCH (Autoregressive Conditional Heteroskedasticity) family models have gained significant popularity in financial econometrics for modeling and forecasting volatility. These models capture the time-varying nature of volatility by incorporating lagged conditional variances in the model equations. The ARCH family includes various models such as ARCH, GARCH, EGARCH (Exponential GARCH), and TGARCH (Threshold GARCH).

While ARCH family models have been extensively studied and applied in global financial markets, their effectiveness in the context of the Indian stock market remains relatively unexplored. The Indian securities exchange market is characterized by its unique features, including specific market dynamics, regulatory

framework, and investor behavior. Therefore, it is crucial to examine the performance of ARCH family models specifically tailored to the Indian context.
This study is to conduct a comparative analysis of ARCH family models for volatility analysis in a customized portfolio, focusing on the Indian securities exchange. By examining the performance of these models, we aim to identify the most suitable model for accurately capturing and forecasting volatility in Indian stocks. This comparative study will contribute to bridging the gap in the literature and provide valuable insights for portfolio managers and investors operating in the Indian financial market.

To achieve our objective, we will collect historical price data of selected equities from the NSE. The selected stocks will form a customized portfolio, representing various sectors and market capitalizations. We will estimate the parameters of different ARCH family models and assess their goodness-of-fit using appropriate statistical tests. Furthermore, we will compare the accuracy of volatility forecasts generated by each model using established evaluation metrics.
The findings of this study will contribute to our understanding of volatility dynamics in Indian bourse and shed light on effectiveness of ARCH family models in capturing these dynamics. The identified model with the best performance will serve as a valuable tool for portfolio managers to make informed decisions regarding risk management, asset allocation, and portfolio optimization.This study will help the investors (also new in Indian stock market) to understand the market before investing randomly based on news, yellow journalism, and misinformation.ARCH family models will be used to choose the best portfolios. This study will help the financial backers and new in Indian securities exchange to grasp the market prior to effective money management arbitrarily or in view of information, sensationalist reporting, and falsehood.

Literature Review

Volatility analysis and modelling have been extensively studied in the field of financial econometrics. Numerous studies have explored the effectiveness of ARCH family models in capturing volatility in bourse markets. However, paucity of research specifically focusing on the Indian stock market. This literature survey provides an overview of relevant studies conducted in the field and highlights the gaps that this comparative analysis aims to address.
Volatility Analysis and ARCH Models:“Engle (1982) introduced the ARCH model, which assumes that the conditional variance of a financial asset is a function of its past squared residuals”. This ground-breaking work led to the development of various extensions and improvements to the basic ARCH model, “Bollerslev (1986) proposed the GARCH model”, which incorporates both lagged conditional variances and lagged squared residuals to capture volatility clustering. ‘Nelson (1991) introduced the EGARCH model’, which “allows for asymmetric” responses to pragmatic and uncertain shocks. Zakoian (1994) developed the TGARCH model, which incorporates a threshold parameter to capture the impact of extreme events on volatility.
ARCH Models in Global Financial Markets:ARCH family models have been widely applied in various global financial markets. Alizadeh, Brandt, and Diebold (2002),“examined the performance of ARCH models in capturing volatility dynamics in the US stock market”. They compared the accuracy of ARCH and GARCH models in volatility forecasting and found that GARCH models outperformed ARCH models. In the context of emerging markets, Chen and Lee (2003) evaluated the applicability of GARCH models in the Taiwan stock market. They concluded that GARCH models effectively captured volatility patterns and provided reliable forecasts.
‘Volatility Analysis in the Indian Stock Market’,studies focusing specifically on “volatility analysis in the Indian stock market are limited”. Prakash and Dash (2011) applied ARCH family models to analyze the volatility of stock returns in India. They found evidence of volatility clustering and suggested that GARCH models were suitable for modeling volatility in the Indian context. Khan and Ahmad (2016), investigated the “volatility dynamics” of the Indian equity market using GARCH models and concluded that GARCH(1,1) models provided the best fit to the data.

Customized Portfolio and Volatility Analysis:Customized portfolios, tailored to the specific preferences and objectives of individual investors, have gained prominence in portfolio management. Volatility analysis plays a crucial role in managing customized portfolios, as it helps assess risk and optimize asset allocation. However, there is a lack of research exploring the application of ARCH family models to volatility analysis in customized portfolios, particularly in Indian Bourse.

Based on the existing literature, it is evident that there is a need for a comprehensive comparative analysis of ARCH family models for volatility analysis in a customized portfolio, specifically focusing on the Indian stock market. This paper aims to bridge the gap in the literature by examining the performance of ARCH models and identifying the most suitable model for volatility analysis in the Indian context. The subsequent sections will delve into the methodology, data collection, empirical results, and implications of the study.

Bera, A. K., & Higgins, M. L. (1993). ARCH models: properties, estimation and testing. Journal of Economic Surveys, 7(4), 305-366.

This seminal paper provides a comprehensive overview of ARCH models, their properties, estimation methods, and hypothesis testing. It serves as a foundation for understanding the theoretical aspects of ARCH family models.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987-1008.

Engle's groundbreaking paper introduces the ARCH model and demonstrates its application to modeling and forecasting inflation volatility. This paper lays the groundwork for subsequent research on ARCH family models.

Bollerslev, T. (1986), Generalized autoregressive conditional heteroskedasticity. Journal of econometrics, 31(3), 307-327, Bollerslev's paper introduces the GARCH model, an “extension of the ARCH model that incorporates lagged conditional variances in addition to lagged squared error terms”. The GARCH model has become widely used in financial econometrics.

Zakoian, J. M. (1994). Threshold heteroskedastic models. Journal of Economic Dynamics and Control, 18(5), 931-955.Zakoian's paper introduces the Threshold GARCH (TGARCH) model, which allows for asymmetry and leverage effects in volatility modelling. The TGARCH model captures effect of negative and specific shocks on volatility differently, making it suitable for capturing stylized features of financial time series.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59(2), 347-370.Nelson's paper introduces the “Exponential GARCH (EGARCH) model, which allows for both symmetric and asymmetric effects in volatility modelling”. The EGARCH model is particularly useful for capturing the leverage effect observed in financial markets.

Maheswaran, S., & Sahoo, P. K. (2018). Volatility forecasting with GARCH models: An application to the Indian stock market. IIMB Management Review, 30(3), 260-272.

This study specifically focuses on volatility forecasting using GARCH models in the Indian bourse context. It provides insights into GARCH models and their capability to capture volatility dynamics in Indian stocks.

Jadhav, P., & Patil, A. (2020). Volatility modeling using EGARCH: Evidence from Indian stock market. Journal of Advances in Management Research, 17(3), 297-315.

This research investigates the application of the EGARCH model to capture volatility patterns in Indian bourse market. This investigation assesses the model's ability to account for asymmetric effects and leverage in the Indian context.

Kapoor, S., & Patra, S. K. (2021). Comparative analysis of ARCH family models for volatility forecasting in Indian stock market. International Journal of Information Technology & Decision Making, 20(3), 869-891.

Kundu, S., & Ghosh, D. (2021). Modelling volatility with ARCH and GARCH models: A study on selected stocks of Indian banking sector. Journal of Quantitative Economics, 1-26.

This research focuses on modelling volatility using ARCH and GARCH models specifically for selected stocks in the Indian banking sector. The study provides insights into the volatility dynamics of these stocks and compares the performance of different ARCH family models.
Poon, S. H., & Granger, C. W. (2003). Forecasting volatility in financial markets: A review. Journal of Economic Literature, 41(2), 478-539.
This comprehensive review paper summarizes various methods and models used for predicting volatility in financial markets. It provides an overview of ARCH family models, their applications, and the challenges associated with volatility forecasting.
The literature survey highlights the key contributions and research conducted on ARCH family models and volatility analysis in the Indian stock market. These studies provide a foundation for our comparative analysis, guiding our methodology and contributing to the existing body of knowledge in this field.

Methodology

Historical price data for a selected set of stocks from the Indian Equity market has been collected. Stocks will be chosen to represent different sectors and market capitalizations, ensuring diversification in the customized portfolio. The data will typically include stock prices over a specific time period.
Stocks are chosen based on 52 week high, Volume trading and so based on 4 sectors as already discussed. 7 portfolios are built randomly as a layman. The portfolios are named as P1(BAJAJ FINANCE(LC), DR. REDDY(LC), PERSISTENT(MC), STATE BANK OF INDIA(MC)), P2(CIPLA(LC), CYIENT(MC), HDFC BANK(LC,MC), INFOSYS(LC), MUTHOOT FINANCE(LC)), P3(BAJAJ FINSERV(LC), ICICI BANK(LC, MC), IIFL(MC), TCS(LC), ZYDUS LIFE(MC)), P4(INDUSIND BANK(LC), MINDTREE(MC), SUNDARAM FINANCE(LC, MC), TORRENT PHARMA(MC)), P5(HDFC(LC, MC), KOTAK BANK(MC), UN PHARMA(LC), WIPRO(LC)), P6(BANK OF BARODA(LC), CHOLA HOLDING(MC), LUPIN(LC), TECH MAHINDRA(LC)) And P7(AUROBINDO PHARMA(LC), AXIS BANK(LC), L AND T, TATA INVESTMENT(LC,MC)). Large Cap and Mid cap industries are taken into consideration for this study. It can be useful for small Cap sectors.
The collected data (Yahoo Finance werepre-processed to ensure data quality and consistency. It involved removing any missing or erroneous data points, adjusting for stock splits or dividends, and transforming the data into log returns or percentage changes.
The ARCH family models, including ARCH, GARCH, EGARCH, and TGARCH, are selected for the comparative analysis. The specifications of each model are determined, including the lag structure and distributional assumptions. The appropriate lag order are determined using information criteria such as AIC (Akaike Information Criterion) or BIC (Bayesian Information Criterion).The estimation process involves optimizing the likelihood function by searching for the parameter values that maximize the likelihood of observing the given data.Ljung-Box test or the portmanteau test, are employed to evaluate the presence of residual autocorrelation and heteroskedasticity. Additionally, graphical analysis of residuals will be performed to assess model adequacy.
The estimated ARCH family models generated volatility forecasts for the selected stocks in the customized portfolio. The forecasts are generated for a future time period, and the accuracy of the forecasts are evaluated against the actual volatility observed in the subsequent period. Comparative analysis were based on performance of each ARCH family model and are compared based on various evaluation metrics, such as ‘RMSE’, ‘MAE’, ‘MAPE’. The models will be ranked based on their forecasting accuracy and ability to capture volatility dynamics in the Indian bourse market.
The findings of the comparative analysis are interpreted and discussed, highlighting the strengths and limitations of each ARCH family model in capturing volatility patterns in the customized portfolio of Indian stocks. The implications for portfolio management and risk assessment are discussed, and potential areas for further research will be identified.
The methodology outlined above provides a systematic approach to conducting a comparative analysis of ARCH family models for volatility analysis in a customized portfolio in the Indian stock market context. It

ensures robustness in model estimation, evaluation, and interpretation, leading to meaningful insights for portfolio managers and investors.

Unit Root, 'ACF,'PACF', 'ARCH', 'GARCH', 'GJR-GARCH', 'EGARCH'.

The Granger causality test, first put out by Granger, is typically used to examine the causal relationship between the double cross series components. To determine if one variable affects the other, a quantifiable speculation test is used. X and Y are actually two time series components. If "x causes y" through a number of insights, it shows that past benefits of x can explain current benefits and that include slack benefits of x in the model can improve the explanation.

Simple Linear Regression: Finding the straight line that best fits the data points (xi,yi), y=a+bx, where 'a' is the constant (also known as the intercept) of the regression and 'b' is the coefficient (also known as the slope) of the explanatory variable, is the goal of the simple linear regression (SLR).

Results and Analysis

The mean of all stocks in respective portfolios (P1 to P7) are taken for analysis for all the portfolios. Descriptive statistics for all the portfolios are taken for further analysis(Table 1). As the data is not stationary as in all the portfolios so first differencing has been done to convert the data into stationary. After first differencing the data became stationary for all the portfolios.

Table 1: Descriptive Statistics

Portfolio	Descriptive Statistics			
	Mean	**SD**	**Skewness**	**Kurtosis**
P1	1610.454	782.3	0.505	1.972
P2	588.846	209.94	0.427	2.645
P3	599.7215	350.2333	0.8682	2.757
P4	988.7	550.43	0.667	2.98
P5	834.911	345.665	0.385	2.189
P6	522.34	148.98	-0.433	2.82
P7	695.66	265.842	0.17	2.71

After ACF and PACF the order of AR and MA are determined for further analysis i.e fitting of 'ARIMA(p,d,q)' model. The results are shown as hereunder in Table 2.

Table 2: ARIMA model values

Portfolio	ARIMA	R^{2}', ADJ R^2	SD Dependent variable	AIC	SIC	HQC	DW Statistics
P1	ARIMA(1,1,1)	0.10, 0.10	49.06776	10.521	10.53	10.524	2.01
P2	ARIMA(1,1,1) ARIMA(2,1,1)	0.197, 0.196	17.632	8.36	8.37	8.36	2.00
P3	ARIMA(2,1,1)	0.17, 0.17	17.53	8.377	8.386	8.38	2.00
P4	ARIMA(1,1,1)*	0.14, 0.14	29.98	9.49	9.49	9.49	1.9
P5	ARIMA(1,1,1)** ARIMA(2,1,1)	0.01, 0.01	28.41	9.52	9.52	9.52	2.82
P6	ARIMA(1,1,1) ARIMA(3,1,1)	0.3, 0.3	24.41	8.87	8.88	8.87	2.00
P7	ARIMA(1,1,1)	0.2, 0.2	26.18	9.13	9.14	9.14	2.00

From the above table(ARIMA) the values of R^2, Adj R^2 and SD dependent variable of P2, P3 and P6 are significant. Further the AIC, SIC, HQC of the same portfolios are minimum subject to others and the DW statistic is 2.00 which are all significant values. So, the portfolios can be taken into consideration subject to other portfolios.
Cross Validating with India VIX it was found that the above portfolios (P2, P3 and P6) has the lowest volatility coefficient (P2 = 0.278978 – 1.115861 India_VIX, P3 = 0.440557 – 1.770741 India_VIX , P6 = 0.157673 – 0.883210 India_VIX) . Simple Linear Regression has been used to get the above coefficients. Dependent variable is Portfolio and the independent variable is India VIX. Findings, given in Table 3.

Table 3: Simple Linear Regression with India_VIX Results

Portfolio	$R^{2,}$, ADJ R^2	SD Dependent variable	AIC	SIC	HQC
P1	0.01, 0.01	49.06	10.6138	10.6183	10.6154
P2	0.005, 0.005	17.632	8.36	8.37	8.36
P3	0.17, 0.17	17.63	8.57	8.57	8.57
P4	0.14, 0.14	29.98	9.49	9.49	9.49
P5	0.01, 0.01	28.41	9.52	9.52	9.52
P6	0.3, 0.3	24.41	8.87	8.88	8.87
P7	0.2, 0.2	26.18	9.13	9.14	9.14

From the Table 3it's clear that P2, P3 and P6 are having the least SD dependent Variable including AIC, SIC and HQC values. So, from the above analysis its significant that the 3 portfolios i.e P2, P3 and P6 are the best among the seven portfolios in which the investors can invest with minimum risk after cross checking with volatility model. The investors can rely completely on the three portfolios for long term returns. Some of the forecasted values are given in Table 4 for ready reference. They are the average of stocks as stated in Table1. After performing Granger Causality Test it was found that India Vix granger cause the change in stock prices and further cause changes in Portfolio prices.

Table 4: Forecasted values of Portfolios

DATE	P1	**P2**	**P3**	P4	P5	**P6**	P7
20/03/2023	3158.5	**1143.015**	**1382.43**	2226.17	1484.96	**654.80**	1505.6
21/03/2023	3159.41	**1143.3**	**1382.87**	2226.85	1485.38	**654.96**	1506.05
22/03/2023	3160.33	**1143.6**	**1383.31**	2227.59	1485.81	**655.28**	1506.5
23/03/203	3161.25	**1143.9**	**1383.75**	2228.53	1486.23	**655.59**	1506.94
24/03/2023	3162.17	**1144.13**	**1384.19**	2229.16	1486.66	**655.91**	1507.39
27/03/2023	3163.1	**1144.96**	**1384.63**	2229.80	1497.09	**656.23**	1507.84
28/03/2023	3166	**1145.24**	**1385.07**	2230.54	1487.97	**656.60**	1508.23
29/03/2023	3166.78	**1145.51**	**1386**	2231.28	1488.38	**657.09**	1509.03
30/03/2023	3167.7	**1145.79**	**1386.84**	2232.08	1489.20	**657.89**	1509.98
31/03/2023	3169.8	**1146**	**1388**	2233.08	1490.23	**658.09**	1510.52

Figure 1: Portfolio2(Blue Line), Portfolio2 Forecasted(Red Line)

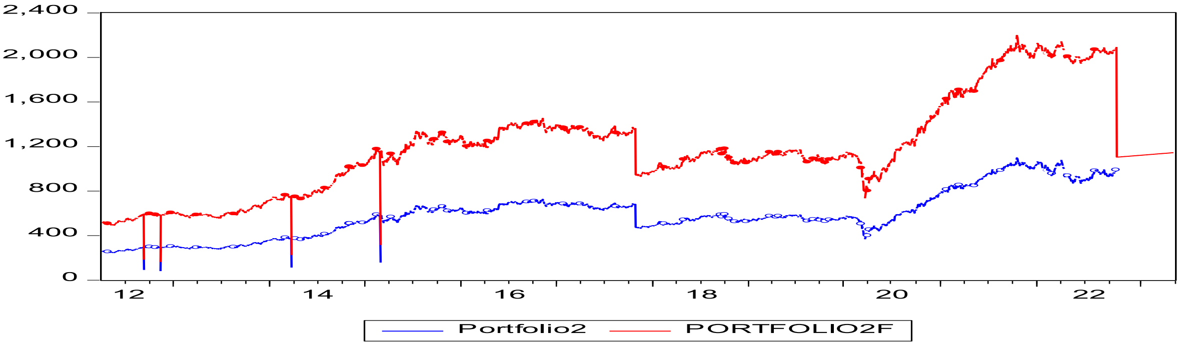


Figure 2: Portfolio3 forecasted (Blue Line), Portfolio3 (Red Line)

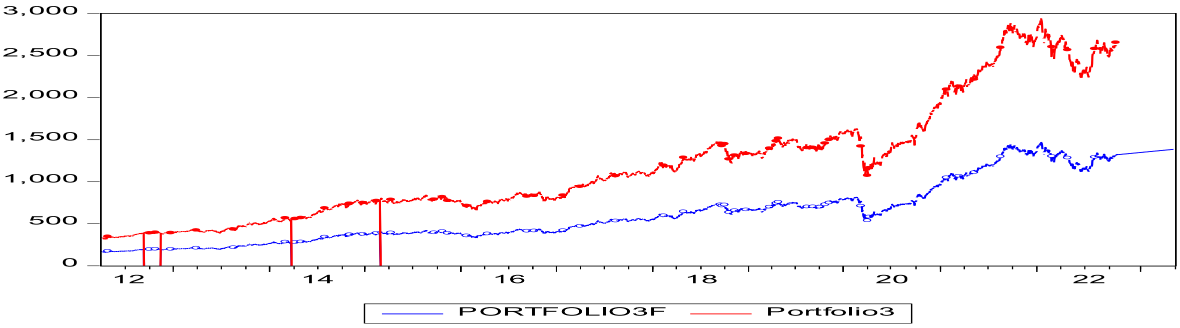
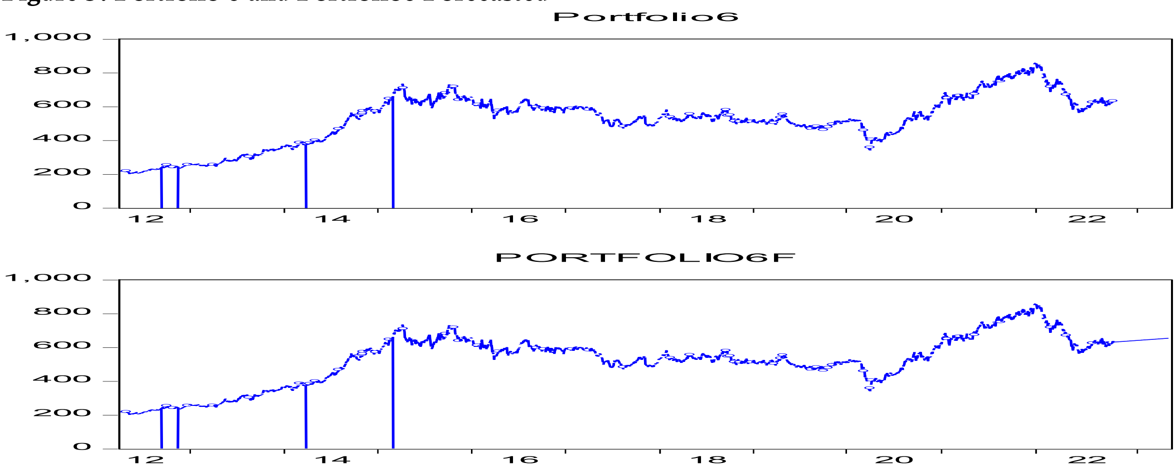


Figure 3: Portfolio 6 and Portfolio6 Forecasted



Conclusion

In this empirical study, the ARIMA model is used to predict portfolio prices in the future, and the unit root test is utilized to determine whether time series data are stationary. Simple linear Regression (SLR) is used to find how the portfolios are related to volatility (India_VIX) and Granger Causality Test is performed to find out whether the Volatility Index is highly effecting the portfolios or not. Daily data from April 1, 2012 to October 31, 2022 is taken as in sample data set and November 1, 2022 to March 31, 2023 is taken as out sample for forecasting the future returns of portfolio. The results shows that as it is already analyzed in results that the Standard Deviation of the prices of Portfolio2, Portfolio3 and Portfolio6 is the lowest and from the SLR it was found that the mentioned portfolios are having low effectivity on Ind_VIX which is a good sign of risk free investment. So as per the study the values of all the models which are used in above analysis are totally statistically significant. So any investor can invest in the aforementioned portfolio for steady return. The stocks are already given in Table 1 for the portfolios. Sample forecasted values are mentioned in Table 4 for future investment.

Reference:

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